ISSN 2959-6157

Bi-Directional Optimization of V2G Strategy Based on Multi-Objective Optimization: Balancing Grid Load and Reducing Electric Vehicle Charging Costs

Yilin Liu

Mechanical Science and Engineering, Dresden University of Technology, 01062, Germany
lyl8157369@gmail.com

Abstract:

With the rapid increase in the number of electric vehicles (EVs), vehicle-to-grid (V2G) technology plays a vital role in reducing the burden on the power system. This technology optimizes network load distribution through a two-way charging mechanism and effectively alleviates network load fluctuations. However, potential negative impacts on EV battery life should also be a cause for concern. Furthermore, the technology does not fundamentally change the charging behavior of electric vehicles. Against this background, this study proposes a multi-objective optimization strategy to adapt electricity price policy to network load fluctuations to control charging behavior. This strategy optimizes battery attenuation, charging costs, and network load fluctuations, aiming to alleviate network load fluctuations while completely solving user concerns about charging and battery maintenance costs. Simulation analysis has verified the effectiveness of this model in reducing grid load fluctuations and balancing user costs.

Keywords: V2G, Peak Shaving and Valley Filling, Multi-objective Optimization, Time-of-Use Pricing Strategy

1. Introduction

In a time of increasing environmental challenges, countries around the world need to address the pressing issue of reducing carbon emissions. Electric vehicles (EVs), with their remarkable emission reduction and environmentally friendly features of using electricity instead of conventional fossil fuels, have become a solution to this problem. With the continuous rise in the number of EVs, challenges primarily include a significant increase in the total load on the electrical grid and potential impacts on the quality and stability of electrical energy[1]. Studies have shown that private EV users typically arrive at their workplaces between 08:00 and 09:00 in the morning and return home during the peak discharge hours of 17:30 to 19:30 in the afternoon. This charging behavior overlaps with the two peak periods of residential electricity use—06:00 to 09:00 in the morning and 17:00 to 21:00 in the evening—placing additional burdens on the grid during peak times[2]. This overlapping time presents unprecedented challenges to the operational stability and power supply quality of the power grid. There is an urgent need to develop effective strategies to deal with these challenges.

Vehicle-to-grid (V2G) technology offers an innovative approach for electric vehicles to serve as adjustable energy loads and transform into distributed energy stations that can transmit power back to the grid. This technology provides a unique advantage by balancing the supply and demand of electricity, thereby enhancing the stability and reliability of the grid. In addition, V2G technology opens up an opportunity for electric vehicle owners to generate additional revenue by delivering power to the grid during peak electricity prices. However, despite the advantages mentioned, V2G technology has also raised some concerns among owners. For many, V2G means their EVs will undergo more frequent charging and discharging cycles. This could accelerate battery aging and thereby affect battery lifespan and overall performance[3]. As a result, many vehicle owners are concerned about the potential negative impacts on the batteries of EVs and are therefore hesitant to connect EVs to the grid during peak electricity consumption periods.

Therefore, this study takes a step further by integrating electricity price policy oversight and battery degradation cost considerations to test the substantial effectiveness of V2G technology in mitigating the conflict between power supply and demand, and reducing grid load peaks and fluctuations. This study aims to demonstrate a charging and discharging strategy by adopting a multi-objective optimization algorithm to achieve a delicate balance between reducing the pressure on the power grid and alleviating the economic burden on users.

2. Construction of the Optimization Model

2.1 Charging and Discharging Model

To simulate whether electric vehicles are connected to the V2G network, this study categorizes the charging and discharging power states of electric vehicles into the following two scenarios:

$$0 < P_{i,t} < P^{char} \quad \forall i \in N - N^{V2G}, \forall t \in \left(t_i^0, t_i^d\right) \tag{1}$$

$$P^{disc} < P_{i,t} < P^{char} \quad \forall i \in N^{V2G}, \forall t \in \left(t_i^0, t_i^d\right) \tag{2}$$

Herein, P^{char} denotes the charging power of the electric vehicle, P^{disc} represents the power released to the grid through V2G, and $P_{i,t}$ is the charging and discharging power of the electric vehicle i at time t. Equation (1) indicates that, within the time interval from t_i^0 to t_i^d, vehicle i is not connected to the V2G network. This means that the charging performance of the vehicle is completely positive. It draws all power from the grid and ensures that the charging power does not exceed the maximum charging limit. On the other hand, equation (2) indicates that electric vehicles are connected to the V2G system within a certain time range. During this period, the energy exchange between the vehicle and the grid is unimpeded, and the amount of electricity exchanged must not exceed the specified maximum charge and discharge power threshold[4].

$$E_i^0 + \sum_{t_i^0}^{t_i^d} ?tP_{i,t}\eta \geqslant E_i^d \quad \forall i \in N \tag{3}$$

$$E_i = E_i^{cap} \cdot SOC_i \quad SOC_{i,min} \leqslant SOC_i \leqslant SOC_{i,max} \tag{4}$$

Equations (3) and (4) establish the constraints for the electric vehicle's battery level, guaranteeing that the battery level of any electric vehicle i at departure is not lower than its minimum required level. Here, E_i^0 represents the initial state of charge, E_i^d denotes the target state of charge, and η stands for the charging efficiency. SOC (State of Charge) represents the percentage of an electric vehicle's battery level[5]. In this study, the maximum and minimum values of SOC are determined to ensure that the battery level of electric vehicles stays within the predefined range of values under all circumstances.

2.2 Based on a Real-Time Variable Electricity Pricing Model

Time-of-use pricing strategies serve as an effective demand-side management tool by identifying peak and off-peak periods in the power grid load curve and setting corresponding electricity prices for different time intervals. As illustrated in Figure 1, the power grid load curve shows significant fluctuations in electricity demand throughout the day[6]de-industrialisation and electrification of heat and transport. These changes are independent of renewable infeed and are not well understood: contemporary studies assume that electricity load curves will retain their current shape, scaling equally in all hours. Changes to this shape will profoundly affect the electricity industry: increasing the requirements for flexible and peaking capacity, and reducing asset utilisation and profitability.","container-title":"Energy","DOI":"10.1016/j.energy.2015.06.082","ISSN":"03605442","journalAbbreviation":"Energy","language":"en","page":"1317-1333","source":"DOI.org (Crossref. In the absence of effective scheduling strategies, the random charging behavior of electric vehicles may further exacerbate the volatility of the total grid load, thereby imposing greater stress on the electrical grid system.

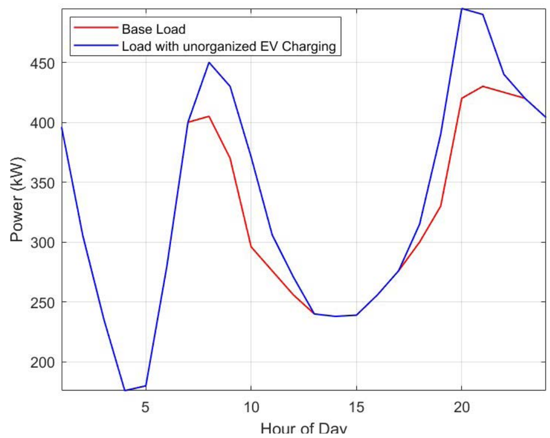

Figure 1 Grid system load

Typically, based on the actual situation of user demand and the power grid load curve, electricity prices are categorized into three distinct time periods: peak, off-peak, and flat[7]. For example, Table 1 illustrates a traditional method of setting time-of-use electricity prices based on peak and off-peak values.

Table 1 peak and valley electricity prices

	Off-Peak	Flat	Peak
Hour	3-6	1-2; 9-18; 23-24	7-8; 19-22
Price	0.3	0.9	1.5

While traditional time-of-use pricing can influence the charging behavior of electric vehicle users to some extent, it lacks the ability for real-time adjustments. Therefore, this study proposes a novel electricity pricing model that dynamically adjusts prices based on changes in real-time total power, as illustrated in equations (5) to (7)[8].

$$P_t = P_t^{base} + P_t^{EV} \tag{5}$$

$$P_t^{EV} = \sum_{i=1}^{N} P_{i,t} \quad (6)$$

$$C(P_t) = aP_t + b \quad (7)$$

In this model, P_t represents the total power of the grid at time t, which is composed of the base power P_t^{base} and the charging and discharging power of electric vehicles P_t^{EV}. As shown in Figure 2, compared to traditional tiered pricing models, pricing based on real-time power can more accurately reflect the real-time load situation of the grid, providing corresponding electricity prices. This approach effectively guides users' charging behavior, allowing for flexible adjustment of the grid load.

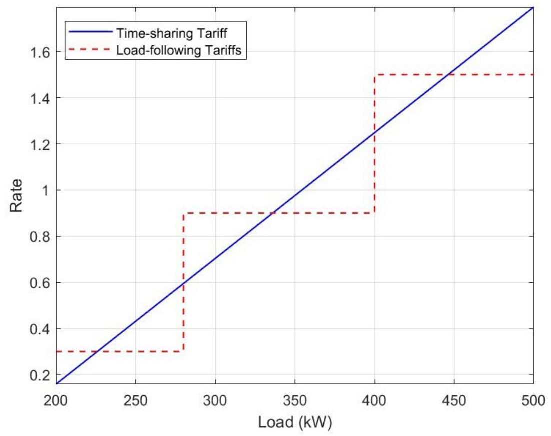

Figure 2 Time-of-Use pricing and power-varying pricing

2.3 Basic Parameter Settings

Considering the typical distribution of battery capacities in the market, most electric vehicles have battery capacities concentrated in the range of 40 to 75 kilowatt-hours (kWh). For example, the battery capacities of the Hyundai Kona Electric and Tesla Model 3 produced in 2019 are 64 kWh and 60 kWh, respectively[9]. Therefore, in the simulation model of this study, 60 kWh is selected as the average battery capacity for simulation. In terms of the use and charging strategies of electric vehicles, to protect the battery life and maintain its performance, the SOC of most electric vehicles is usually kept within a range of 20% to 80%. This practice helps avoid the battery from being in a fully charged or excessively discharged state for an extended period, thus prolonging the battery's lifespan. Moreover, many users tend to start charging when the battery's SOC drops to about 20%, which is significant for designing effective charging strategies and grid management measures[10]. To realistically reflect the charging habits of electric vehicle users, this study sets the minimum SOC of the electric vehicle battery at 0.1 and the maximum SOC at 0.9 in the simulation model. This setting aims to simulate the charging strategies adopted by electric vehicles in reality to avoid over-discharging or overcharging the battery. In the current market, the output power of V2G charging facilities is generally around 15 kW. Therefore, in this simulation, the maximum charging and discharging power is set to 15 kW to align with the performance characteristics of V2G charging stations in reality.

Table 2 presents the fundamental parameter settings of electric vehicles in the simulation study, where E_i^0 represents the initial battery power of the electric vehicle, and E_i^d represents the battery power required after charging is completed. t_i^0 is the time when the EV is connected to the V2G network, and t_i^d is the time when the vehicle disconnects from the network[11].

Table 2 Basic parameters of electric vehicles

Parameters	Value	Parameters	Value
E_i^{cap}	60	η	0.95
P^{disc}	-15	T	24
P^{char}	15	$SOC_{i,min}$	0.1
E_i^0	N(0.2×60, 2)	$SOC_{i,max}$	0.9
E_i^d	N(0.85×60, 2)	a	0.00545
t_i^0	N(8:00, 2)	b	-0.9314
t_i^d	N(20:00, 2)		

3. The Objective Function for Optimization

3.1 The peak-to-valley difference and fluctuation of the integrated load

The objective function F_1, as shown in Equation (8), aims to minimize the peak-to-valley difference of the total power in the grid after optimization to reduce the load fluctuations of the power grid[12].

$$F_1 = min(max(P_t) - min(P_t)) \tag{8}$$

Equation (9) is used to calculate the average total power. Meanwhile, the objective function F_2, according to Equation (10), aims to minimize the variance of the total power after optimization. This goal is to reduce the power fluctuations across the entire power grid, thereby enhancing the stability of the electricity supplied by the grid.

$$P_{avg} = \frac{1}{T}\sum_{t=1}^{T}\left(P_t^{base} + \sum_{i=1}^{N} P_{i,t}\right) \tag{9}$$

$$F_2 = min\frac{1}{T}\sum_{t=1}^{T}\left(P_t - P_{avg}\right)^2 \tag{10}$$

3.2 User Charging Costs and Battery Degradation Costs

The objective function F_3 is shown in equation (11), which aims to minimize the total cost incurred by users for charging electric vehicles[13]. When the total power P_t at a certain moment exceeds the base power P_t^{base}, it indicates that electric vehicles are drawing electricity from the grid for charging; conversely, when the optimized total power P_t is lower than the base power P_t^{base}, it indicates that electric vehicles are supplying electricity to the grid. Based on this direction of energy flow, the user's charging costs and the benefits obtained by supplying electricity to the grid through V2G technology can be calculated.

$$F_3 = min\sum_{t=1}^{T}\int_{P_t^{base}}^{P_t} C(P_t)\,dP = min\sum_{t=1}^{T}\int_{P_t^{base}}^{P_t}(aP_t + b)\,dP \tag{11}$$

The battery degradation model caused by electric vehicle charging, as described in the referenced literature, is represented by Equation (12)[14]. Here, parameters a, b, and c are values determined by battery characteristics. In the simulation, the parameter values provided in the literature were directly utilized. The specific numerical values of parameters a, b, and c are listed in Table 3. Objective function F_4, calculated according to Equation (13), considers the battery degradation costs that all electric vehicles incur from charging within a 24-hour period. This model and objective function configuration take into account the economic costs associated with the impact of electric vehicle charging on battery health. The goal is to reduce the cost burden of battery degradation by implementing optimized charging strategies.

$$E(c_{Batt}) = a\bullet\left(P_t^{EV}\right)^2 + b\bullet P_t^{EV} + c \tag{12}$$

$$F_4 = min\sum_{t=1}^{T} E(c_{Batt}) \tag{13}$$

Table 3 Battery degradation factor

a	b	c
0.004	0.075	0.003

3.3 Single Objective Treatment of Multi-Objective Optimization

To facilitate the treatment of multi-objective optimization problems and simultaneously consider the importance of different objective functions, this study converts the multi-objective problem into a single-objective optimization problem. This transformation is achieved by normalizing and introducing weighting coefficients for the objective functions, as demonstrated by the overall optimization objective function shown in Equation (14).

$$F = min(w_1\bullet\frac{F_1}{F_{1M}} + w_2\bullet\frac{F_2}{F_{2M}} + w_3\bullet\frac{F_3}{F_{3M}} + w_4\bullet\frac{F_4}{F_{4M}}) \tag{14}$$

Theoretically, F_{1M} to F_{4M} should correspond to the maximum value that each objective function can achieve. This simulation adopts the extreme load conditions during unscheduled charging of electric vehicles, as illustrated in Figure 1, as a reference to determine the specific values of F_{1M} to F_{4M}. These values are provided in Table 4.

Table 4 Maximum values setting

F_{1M}	F_{2M}	F_{3M}	F_{4M}
319	8866	558	3650.4

Here, w_1 to w_4 respectively represent the weighting coefficients of the four objective functions. The specific settings of the weighting coefficients in this simulation are listed in Table 5.

Table 5 Weighting factors setting

w_1	w_2	w_3	w_4
0.4	0.2	0.2	0.2

4. Simulation cases

This study utilizes the typical daily load of residential buildings as the fundamental data and uses the Matlab environment in conjunction with Yalmip and Cplex tools to solve the issue. In the experiment, a total of 10 electric vehicles participated in the charging process, of which 5 electric vehicles are planned to join the V2G network.

Figure 3 illustrates the initial network load, the total network load with electric vehicles being charged at irregular intervals, and the optimized network load post-optimization. Additionally, it provides an overview of the entire charging and discharging activities of an electric vehicle throughout the day.

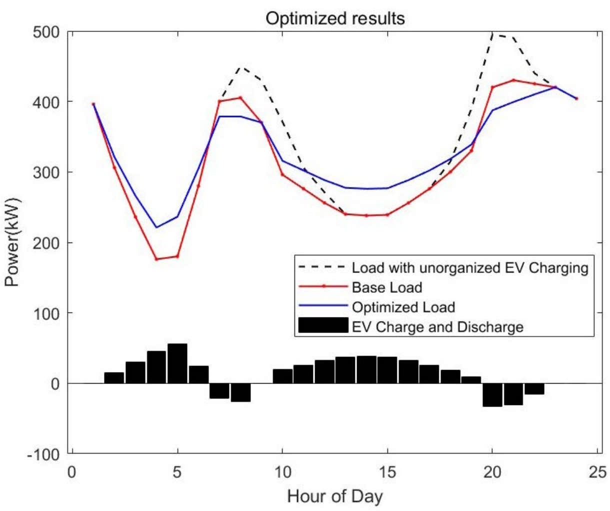

Figure 3 Optimized grid system load

From the overall analysis of Figure 3, it is evident that the peak-to-valley difference of the optimized total load has significantly reduced. Additionally, there is an increase in load during off-peak periods and a decrease in load during peak periods, indicating the successful implementation of peak shaving and valley filling in the grid load.

Figure 4 displays the electricity price trend chart based on real-time total load fluctuations. Compared to traditional fixed time-of-use pricing, dynamically adjusted electricity prices based on load variations can more accurately reflect the actual charging demands of the system and provide more reasonable pricing. This dynamic pricing strategy helps guide user charging behavior more effectively, encouraging users to charge during periods of lower grid load. This approach helps avoid the concentration of charging during peak periods and optimizes the distribution of grid load.

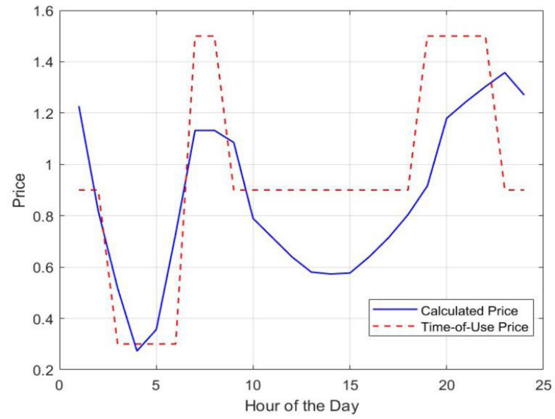

Figure 4 Comparison of two electricity pricing models

Figure 5 illustrates the charging and discharging activities of the 10 electric vehicles over a 24-hour period. It can be observed that the SOC of all electric vehicles adheres to the predefined boundary conditions, staying within the set minimum and maximum values. Additionally, it addresses the charging needs of electric vehicles and provides detailed observations of the charging and discharging behavior of each electric vehicle over various time periods.

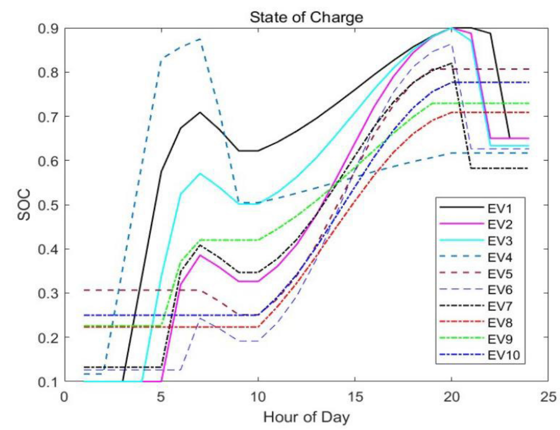

Figure 5 SOC of electric vehicles

The study also compares the results of four objective functions under uncontrolled charging and optimized ordered charging scenarios, which are listed in Table 5.

Table 5 Weighting factors setting

	Peak	Valley	F_{1M}	F_{2M}	F_{3M}	F_{4M}
Before optimization	495	176	319	8866	558	3650
After optimization	420	221	199	5537	251	3179

From the data in the table above, it is evident that the impact on the grid is significant when electric vehicles charge without control. This can lead to increased peak-to-valley differences, causing grid fluctuations. Additionally, if users charge their devices simultaneously in a concentrated manner during the same time period, it can result in higher charging costs. Through the multi-objective optimization model constructed in the study, the peak-to-valley difference and fluctuations of the system are significantly reduced compared to uncontrolled charging, resulting in a smoother grid load curve. At the same time, the costs incurred by users for charging and battery degradation are also significantly reduced.

5. Conclusion

By conducting an in-depth study on the charging behavior of electric vehicles and incorporating grid peak-to-valley values, mean square deviation, user charging costs, and battery degradation costs into the optimization objectives, this study has meticulously adjusted the charging and discharging power of electric vehicles in Vehicle-to-Grid (V2G) networks. Through optimization, improvements in the target outcomes have been achieved, and more rational time-of-use pricing schemes can be proposed based on the optimization results. The case analysis of this study yields several key conclusions:

1) In the absence of proper scheduling, uncontrolled charging of a large number of electric vehicles can lead to an increase in the peak-to-valley difference in the grid, thereby adversely affecting the grid's stability.

2) Compared with relying solely on fixed time-of-use prices, dynamically adjusting real-time prices based on load fluctuations can more effectively guide users to charge at optimal periods. In addition, the real-time pricing scheme derived from the optimization results will also assist the power grid in formulating a more scientific and reasonable pricing strategy.

3) By establishing a multi-objective optimization model that considers both grid load fluctuations and user expenditures, simulation results demonstrate that achieving a win-win situation for both the grid and electric vehicle users is feasible under reasonable scheduling and pricing strategies.

References

[1] ZHANG S, SUN Y. Analysis for V2G Response Cost of EV Aggregator Considering Time-of-use Tariffs and Battery Wear[J]. Proceedings of the CSU-EPSA, 2017, 29(11): 39–46.

[2] ZHANG Q, LI C, ZHOU L, et al. Load frequency control considering dynamic change of real-time controllable EV energy[J]. Electric Power Automation Equipment, 2017, 37(8): 234–241.

[3] ZHANG Q, DENG X, YUE H, et al. Coordinated Optimization Strategy of Electric Vehicle Cluster Participating in Energy and Frequency Regulation Markets Considering Battery Lifetime Degradation[J]. Electric Power Automation Equipment, 2022, 37(1): 72–81.

[4] WU J, AI X, HU J. Methods for Characterizing Flexibilities from Demand-Side Resources and Their Applications in the Day-Ahead Optimal Scheduling[J]. TRANSACTIONS OF CHINA ELECTROTECHNICAL SOCIETY, 2020, 35(9): 1973–1984.

[5] XU J, AI X, JIN P, et al. Research on Charging and Discharging Control Strategy for Regional EV[J]. East China Electric Power, 2011, 39(12): 2045–2049.

[6] Boßmann T, Staffell I. The shape of future electricity demand: Exploring load curves in 2050s Germany and Britain[J]. Energy, 2015, 90: 1317–1333.

[7] OU M, CHEN Z, TAN Y, et al. Optimization of electric vehicle charging load based on peak-to-valley time-of-use electricity price[J]. JOURNAL OF ELECTRIC POWER SCIENCE AND TECHNOLOGY, 2020, 35(5): 54–59.

[8] HUANG X, CHEN J, XIE Q, et al. The Influence of Users' Charging Selection on Charging Schedule of Power Grid[J]. TRANSACTIONS OF CHINA ELECTROTECHNICAL SOCIETY, 2018, 33(13): 3002–3011.

[9] Dixon J, Bell K. Electric vehicles: Battery capacity, charger power, access to charging and the impacts on distribution networks[J]. eTransportation, 2020, 4: 100059.

[10] MENG X, LIANG S, ZHANG T, et al. Big Data Analysis and Application on User Charging Behaviors for New Energy Vehicles[J]. Automotive Digest, 2021(3): 34–39.

[11] HE C, GENG T, XU X, et al. Research on grid frequency regulation using schedulable capacity of electric vehicles[J]. PowerSystemProtectionandControl, 2015, 43(22): 134–140.

[12] Zhaoyun Z, Linjun L, Xinghua W. Researh on dynamic time-sharing tariff orderly charging strategy based on NSGA2 in PV-Storage-Charging stations[J]. Electric Power Systems Research, 2023, 225: 109784.

[13] Malik A, Urooj A. Electricity Tariff Design: A Survey[J]. The Pakistan Development Review, Pakistan Institute of Development Economics, Islamabad, 2022, 61(4): 663–680.

[14] WANG Z, LUO X. Revenue-optimization model for electric-vehicle charging stations considering battery degradation and dynamic charging characteristics[J]. Journal of Transportation Engineering and Information, 2023, 21(3): 13–30.